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REGIONAL BLUE AND GREEN WATER BALANCES AND USE BY SELECTED CROPS IN THE U.S.[1]

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ABSTRACT: The availability of freshwater is a prerequisite for municipal development and agricultural production, especially in the arid and semiarid portions of the western United States (U.S.). Agriculture is the leading user of water in the U.S. Agricultural water use can be partitioned into green (derived from rainfall) and blue water (irrigation). Blue water can be further subdivided by source. In this research, we develop a hydrologic balance by 8-Digit Hydrologic Unit Code using a combination of Soil and Water Assessment Tool simulations and available human water use estimates. These data are used to partition agricultural groundwater usage by sustainability and surface water usage by local source or importation. These predictions coupled with reported agricultural yield data are used to predict the virtual water contained in each ton of corn, wheat, sorghum, and soybeans produced and its source. We estimate that these four crops consume 480 km^3 of green water annually and 23 km^3 of blue water, 12 km^3 of which is from groundwater withdrawal. Regional trends in blue water use from groundwater depletion highlight heavy usage in the High Plains, and small pockets throughout the western U.S. This information is presented to inform water resources debate by estimating the cost of agricultural production in terms of water regionally. This research illustrates the variable water content of the crops we consume and export, and the source of that water.

(KEY TERMS: modeling; water use; SWAT; blue water; green water.)

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INTRODUCTION

The availability of freshwater underpins human civilization. Water availability dictates the distribution of human population and agricultural production across the United States (U.S.). The distribution of water resources is variable, subject to local climate, topography, and geology. Municipalities and agriculture often compete over this limited resource. A great deal of resources are employed to move water from one location to another, or drill wells to pump it from underground. These factors make water very much a local issue. It is critical that we understand local sources and their sustainability if we want to wisely allocate water resources.

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Virtual Water

Agricultural consumption accounts for 90% of the global water usage (Rost *et al.*, 2008). The primary use is irrigation, but water is also consumed by livestock production and the processing of agricultural products. The quantity of water required to produce a particular product is embodied in the concept of virtual water (Allan, 2003). Virtual water is not contained within a product but is the amount of water required to produce it. The concept of virtual water content (VWC) has been applied to agricultural crop production extensively (Hanasaki *et al.*, 2010; Liu and Yang, 2010; Siebert and Döll, 2010; Sun *et al.*, 2012; Mubako and Lant, 2013).

Global and regional trade in agricultural commodities has been evaluated in terms of virtual water (Hoekstra and Hung, 2005; Mekonnen and Hoekstra, 2011; Sun *et al.*, 2012; Mubako and Lant, 2013). These analyses utilize trade and production data to identify the net movement of grain from one location to another. The total amount of virtual water contained in these exchanged grains has been estimated to be 556-979 km^3/yr (Hanasaki *et al.*, 2010).

The VWC of a particular grain also depends upon the location and method of its production. Global estimates for corn by country range from 370 to 1,222 m^3/ton (Zwart and Bastiaanssen, 2004; Hoekstra and Chapagain, 2008; Hanasaki *et al.*, 2010; Mekonnen and Hoekstra, 2011). Within a single country there is even more variability, as the area contribution to the average are smaller. Local climatic extremes are subject to less averaging at smaller spatial scales. Mubako and Lant (2013) estimated VWC by state for corn to be 278-1,558 m^3/ton within the U.S. To accurately represent the VWC of a crop from a particular region, the local conditions must be considered. Most large-scale efforts to estimate crop VWC use simulation models to some degree.

Sun *et al.* (2012) used the Food and Agriculture Organization CROPWAT 8.0 model (FAO, 2013), which is based on the Penman-Monteith method (Monteith, 1965), coupled with crop yield statistics to estimate VWCs of crops in China. Mubako and Lant (2013) also used CROPWAT to estimate evapotranspiration (ET) and in combination with yield statistics predicted VWC of crops by state within the U.S.

Blue and Green Water

The VWC of a crop alone does not adequately describe the real cost of production in terms of water resources. VWC does not consider the source of water nor its local value. The relative value of water is tied to both its local abundance (or lack thereof) and the effort required to deliver it to the point of consumption. The concept of blue and green water (Ringersma *et al.*, 2003; Falkenmark and Rockström, 2004, 2006) is a useful tool in the assessment of regional water resource availability and use. Water availability has traditionally focused on blue water, which is defined as water which runs off the landscape into streams, rivers, and reservoirs, and groundwater. Blue water has the potential to be captured and conveyed for human use, and may originate from surface waters or aquifers. Precipitation which is held in the soil profile and does not percolate or runoff and is eventually used by plants for ET is referred to as green water. Both green and blue water are consumed in the production of agricultural crops, the relative usage is dependent upon many factors, including whether the crop is irrigated and the local climate. In general, green water is preferred due to its low opportunity cost.

The measurement of blue and green water flows is difficult even within a single field. The quantification of blue water consumption or production requires the measurement of total runoff, aquifer recharge, and irrigation applications. If more irrigation water is consumed than is produced by runoff and aquifer recharge, the field is a net consumer of blue water. Green water measurement requires additional monitoring of precipitation and ET. Unfortunately, field monitoring data are expensive to collect, limiting the number of individual observations available with which to make regional generalizations. In addition, these data may only represent local soils, topography, and weather and crop management at the point of collection, and may be applicable to other fields located hundreds or thousands of kilometers away. Given the limitations of monitoring data, the most sensible approach for large-scale analysis includes hydrologic simulation models.

A variety of models have been utilized by researchers (Rost *et al.*, 2008; Schuol *et al.*, 2008; Faramarzi *et al.*, 2009). Rost *et al.* (2008) used the dynamic global vegetation and water balance model Lund-Potsdam-Jena managed Land (LPJmL) (Bondeau *et al.*, 2007) to evaluate the effects of human-induced land cover change and irrigation on blue and green water resources. LPJmL operates at a daily time step and a 0.5° global grid. Many researchers have opted to utilize the Soil and Water Assessment Tool (SWAT) (Arnold *et al.*, 1998). Schuol *et al.* (2008) used the model to simulate blue and green water availability in the continent of Africa. This SWAT model was calibrated to monitored stream discharge data. Model predictions were used to identify regions of water scarcity for the purposes of national water planning and management. Faramarzi *et al.* (2009) calibrated and validated a SWAT model to predict blue/green water flows in Iran under current conditions. They found that the majority of the primary staple crop (wheat) was produced in water scarce regions, illuminating the venerability of regional food production to climate change and groundwater depletion. Zang *et al.* (2012) developed a SWAT model for a large basin in Northwestern China and calibrated it for current conditions. The calibrated model was altered to represent natural conditions to provide blue/green water benchmarks to aid in water resource management. Glavan *et al.* (2012) used the SWAT model to predict green and blue water flows under past land uses in two Mediterranean basins.

Local blue/green water flows can be used to ascertain the composition of crop VWC. The subdivision of crop VWC into blue and green portions is an especially attractive approach. The virtual blue water content (BWC) of a crop is the most expensive and manageable portion from a water resources perspective. The BWC of a crop is dependent upon how much irrigation was required to produce it, which in turn is dependent on local conditions.

Researchers have again turned to models to perform this analysis. Siebert and Döll (2010) quantified virtual blue and green water contents (GWC) of various crops using the Global Crop Water Model (GCWM) for the period 1998-2002. GCWM operates on a grid of 0.5° utilizing the global land use dataset MIRCA2000 (Portmann *et al.*, 2010). Liu *et al.* (2009) also estimated blue/green components of crop water use for agricultural crops at resolution of 0.5° using the GIS-based Erosion Productivity Impact Calculator model (G-EPIC) (Liu *et al.*, 2007). The SWAT model landscape components were originally based on the (EPIC) (Williams, 1990) model. Mekonnen and Hoekstra (2011) simulated ET on a gridded basis to estimate water usage by 126 primary crops and used CROPWAT 8.0 for another 20 secondary crops worldwide, and subdivided ET into blue and green water fractions. Huang and Li (2010) calculated crop productivity per unit of water consumption in China. SWAT simulated blue and green water flows were coupled with available crop production statistics. The blue/green water use ratio for cereal grains was estimated and found to vary significantly by both crop and location. On average 946 m^3 of water were used to produce 1 ton of grain.

Blue Water Subdivision

Just as blue water is more important from a resource management perspective than green water, there are sources of blue water that are more critical than others. Blue water can be obtained from either surface sources such as reservoirs or pumped from aquifers. The availability of surface and groundwater for irrigation is highly variable, often dictating local agriculture and human settlements. The availability of surface water depends upon proximity to rivers which may be impounded to form reservoirs and/or the construction of canals for distribution or import from distant areas. There must also be sufficient runoff from the landscape upstream to maintain these waters. Likewise groundwater availability depends upon the presence of suitable geologic formations for storage and sufficient recharge from the local landscape. Both surface and groundwater can be overused. The amount of storage in each system (surface and ground) is an important consideration. Groundwater accounts for 30% of the world's freshwater, lakes and rivers account for only 0.27% (Myers, 1993). Groundwater massive storage coupled with its slow rate of replenishment contributes to its overuse.

Using groundwater faster than it is replenished through recharge depletes aquifers and is causing groundwater levels to drop. Estimated groundwater depletion in the U.S. during 1900-2008 totaled nearly 1,000 km^3 (Konikow, 2013). Approximately, one-third of this depletion occurred in the High Plains aquifer system (also known as the Ogallala aquifer) in the west central U.S., a region of intensive grain production and location of the 1930s "Dust Bowl." The vast imbalance between use and recharge make water from these sources essentially nonrenewable and a critical issue in water resource planning.

Research Objectives and Approach

The primary objective of this research is to quantify local water budgets within U.S. 8-digit catchments both comprehensively for the entire landscape, and with a focus of agricultural production. To meet this objective, the VWC of U.S. commodity grains (corn, wheat, soybeans, and sorghum) and the source of this water were spatially simulated. This includes the development of a spatial explicit national level water balance using the SWAT model. Model predictions are combined with national water use data to identify regions where both surface and groundwater usage exceeds total sustainable blue water availability at the local level. SWAT predicted irrigation usage and water balance information were combined with reported crop yields to estimate crop VWC regionally. The VWC of individual crops was partitioned into green water and various sources of blue water. These results identified areas where crops are produced using nonsustainable resources. This information is presented to better inform state and federal water resource strategic water planning.

MATERIALS AND METHODS

General Approach

Most blue/green hydrologic simulations discretize the area of interest into either subbasins or grids. Global simulations are typically grid-based while all SWAT-based studies utilize subbasins. The approach described herein differs significantly from these discretization schemes in an effort to allow the inclusion of very detailed local conditions over a large spatial extent without overwhelming computation requirements.

Typical SWAT applications utilize subbasins which are further discretized into hydrologic response units (HRUs). An HRU is a unique combination of soils, weather, land use, topography, and management within a subbasin. The computational requirements of a SWAT model are directly proportional to the number of HRUs it contains; it is therefore advantageous to use as few HRUs as possible. It is also desirable to include as much detail as possible, which increases the number of HRUs. Cultivated cropland is of particular interest in this study and the level of management data utilized in this research is comparable to detailed small watershed studies, yet the scale is national.

The inclusion of each additional facet of management, such as crop type, use of irrigation, tillage intensity, exponentially increases the number of HRUs required. For example, if two crops (corn and wheat) are present in a subbasin only two HRUs are required. If we consider that a portion of each crop may be irrigated, we must simulate both the irrigated and dryland condition for both, thus four HRUs are needed. If we further consider that each crop may have one of five levels of tillage, 20 HRUs are needed. Factor in tile drains, multiple soils, and topographic conditions, and HRU complexity and computational requirements become unmanageable. The typical approach is to eliminate relatively small HRUs representing atypical conditions (less than some defined threshold) and attribute that HRU's area into a more dominant HRU, although this approach does introduce bias. The sheer number of potential HRUs (tens of millions) required to represent the aforementioned level of detail at the scale of the contiguous U.S. precludes the simulation using SWAT in a single model. We estimate that on the order of 600 GB of RAM would be required to hold such a model.

The application of the SWAT model in this research is based on methods derived from White *et al.* (2015). The SWAT model developed for this application is a collection of millions of individuals fully independent SWAT simulations. Each simulation is a single subbasin model representing a specific land use, soil, location, time, and management. The individual simulations are based on the structure utilized by the Texas Best Management Practice Evaluation Tool (TBET) (White *et al.*, 2012) to represent a single field in SWAT. Each simulation (sample) represents a single site (16 ha) from a population of all potential sites in the U.S. with characteristics defined by the available spatial data. The size of each sample site (16 ha) was selected as a reasonable HRU size by White *et al.* (2012) for field level predictions. This approach allows the consideration of all possible combinations of land use, topography, climate, management, and soils without bias.

Each simulation represents a sample point chosen with a defined set of characteristics. The specific land use, soil, location, time, and management for each sample point are defined by a Monty Carlo-type approach. Each simulation is a sample from the much larger population of all potential HRUs in the U.S. The probability that the sample will have a particular characteristic is based on the distribution of that characteristic as defined by the data sources in Table 1. This can perhaps best be illustrated through an example. First, the location of the sample is established by pseudo-randomly selecting a single USGS 8 digit Hydrologic Unit Code (HUC-8). Although random, the probability that any single HUC-8 will be selected is not the same. Larger HUC-8s have a higher probability of being initially selected, because they comprise more of the U.S. In this way, sampling is not biased due to the nonuniform sizes of each HUC-8. Next the ecoregion and county are selected based on their relative area within the selected HUC. It is necessary to select both a county and HUC-8 to accommodate the differing spatial scale of differing model inputs. Land use is selected based on the distribution of all land uses within the HUC-8. Next, a specific soil and slope is selected based on their relative distribution within the HUC-8. This distribution is derived from national models developed in the Conservation Effects and Assessment Project (CEAP); additional details are available by Santhi *et al.* (2014) and White *et al.* (2014). A single weather station is then selected for the sample at random based on the proximity to the nearby stations; closer stations are selected more often. For cropland samples, tillage, presence of tile drains, and a management operation template are selected based on their respective distribution with the HUC-8.

The probability that any particular combination will be selected as a sample is proportional to the area that a particular combination represents within the U.S. A database of 21 million samples was developed such that samples matching any particular criteria (i.e., county, HUC-8, or land use) can be queried

TABLE 1. SWAT Model Inputs and Categorical Basis for Selection within the Distribution.

Required Model Input	Categorical Distribution Basis
HUC-8	Area
Ecoregion (Omerick III)	Area of ecoregion in selected HUC-8
County	Area of county in selected HUC-8
Land use (crop)	Area of each land use in selected HUC-8
Tiles (cropland only)	Area of tiles in selected HUC-8
Weather station	Distance from HUC-8 centroid to each station
Soil and slope	Area of each combination of soil/land use in CEAP SWAT configuration databases
Irrigation	Fraction of land use type irrigated in selected HUC-8
Tillage class	Fraction of crop type in each tillage class in selected HUC-8
Management operations (cropland)	Random selection from matching crop, tillage class, and county
Management operations (noncultivated)	Defined by HUC-8 in national CEAP model

and summarized to provide relevant predictions for that spatial unit. The number of samples in this database is only important in that with many samples, relatively rare combinations of crop, location, tillage, and other factors are more likely to be represented in the database, and computational time is cheap. It is unlikely that the results of this research would be significantly different with far fewer samples.

Data Sources

Land Use. Land use distribution was based in the 2009 Cropland Data Layer. The data were simplified into 123 categories representing both cultivated and noncultivated land uses resampled as a 90-m grid for the contiguous U.S. The area of each land use within each HUC-8 was calculated. This area is used to calculate the probability that any point selected at random within a particular HUC-8 will be of a certain land use category.

Soils/Slope. Soils and slope were selected from a database of HRU characteristics developed for the CEAP effort. These data were derived by intersecting State Soil Geographic Database (STATSGO) soils (USDA-NRCS, 1992), 2001 National Land-Cover Data Sets (Homer *et al.*, 2007), and Hydrologic Landscape Regions of the U.S. (USGS, 2003). The resulting HRU overlay contained hundreds of thousands of unique combinations. Each combination has a soil, slope, land use, and HUC-8 assignment, and associated coverage area. Combinations which match the HUC-8 and general land use category already selected are potential candidates. The probability that a match candidate will be selected is based on its assigned area from the CEAP database.

Climate. Weather data were derived from the National Oceanic and Atmospheric Administration COOP Cooperative Observer network and WBAN Weather-Bureau-Army-Navy stations from January 1950 to December 2010. An inverse distance weighted interpolation algorithm was used to fill missing observations from the nearest five stations. The exact five stations used varies day by day as there are frequently missing data at the surrounding stations as well. The database contains approximately 19,000 stations. A single climate station was selected for each simulation based on the distance from the centroid of the selected HUC-8 to each candidate weather station.

Irrigation. The fraction of particular crop which is irrigated was derived from USDA National Agricultural Statistics Service (NASS) county level statistics for the period 1990-2008. NASS data contain irrigated and dryland acres per county or district which were used to estimate the fraction of a particular crop which is irrigated. NASS does not report both dryland and irrigated data for many counties in the U.S.; these tend to be located in regions where irrigation is either rare because it is not needed or crops would almost certainly require irrigation, leaving little question as to whether irrigation is appropriate. In these missing counties, crops were assumed to be either entirely irrigated or entirely dryland based on the average county precipitation. A threshold precipitation value was developed for each major crop type; if the county precipitation exceeds the threshold, the crop is assumed to be dryland, otherwise it is assumed irrigated. These values were derived from analysis of counties with irrigation fraction information and associated average precipitation. Threshold values for corn, sorghum, soybeans, and small grains were 650, 450, 700, and 500 mm/yr, respectively. Counties lacking NASS data tended to have precipitation much higher or lower than the thresholds. The fraction of the county under irrigation for a particular crop was used to define the probability that the SWAT simulation would contain an auto-irrigation operation. The actual amount of irrigation in SWAT is based on crop water demands, and varies by crop, soil, and climate.

Tillage Class. The distribution of tillage by crop and by HUC-8 was derived from Baker (2011). These data were aggregated from the county level survey data collected by the Conservation Technology Information Center (CTIC). These contain the fraction of five crops (corn, small grains, cotton, sorghum, and soybeans) in five tillage classes (ridge, mulch, reduced, conventional, and no-till). This fractional area was used to define the probability that the simulation will be assigned a particular tillage classification.

Management. Management comprised all the operations conducted by the producer including tillage, planting, grazing, irrigation, fertilization, and harvest. The individual operations are scheduled by date or heat unit accumulation, and may require additional application or stocking rates or types. Dates, crops, and cultural practices vary by region, making management the most difficult SWAT input to develop. Management for noncultivated land uses was developed by an expert panel of simulation modelers and NRCS personnel at the HUC-8 level associated with the CEAP effort. Cropland management was derived from a database of differing crops and systems which were developed at the county level for the contiguous U.S.

Cultivated crop management templates for each county were derived from management templates developed by the NRCS for the RUSLE2 (Foster *et al.*, 2000) model. These very detailed templates contain operations, implements, and dates relevant to each of the 80 crop management zones, which reflect local climatic and cultural practices. There are approximately 20,000 such templates. Each county in the U.S. was assigned to a particular zone. A significant level of processing was required to utilize these templates for use in SWAT as these models require different data. Changes included, addition of fertilization operations, tillage induce kills, kills to prevent multiple growing crops, equal planting and kill operations, and dovetailing of multi-year operation schedules. Soil tillage intensity ratings were used to assign one of five tillage categories (ridge 10-15, mulch 15-60, reduced 60-100, conventional 100+, and no-till 0-10) to each template. SWAT plant growth-related parameters such as potential heat units to maturity were developed from county weather statistics.

Fertilization rates for major crops were developed by county using NASS agricultural census data. Reported fertilizer usage by crop at the state level for the period 1990-2007 were combined with corresponding reported crop yield. These data were used to calculate fertilizer application per unit of production for corn, cotton, soybean, wheat, and sorghum. For example, we found that 0.019 kg of nitrogen and 0.0072 kg of phosphate were applied to produce 1 kg of corn on average. Fertilization rates for each crop at the county level were estimated for both irrigated and dryland conditions. These fertilizer applicant rates were incorporated into the management database to develop a variety of complete SWAT management templates for differing crops and tillage for each county in the U.S.

A management template was selected for each simulation by querying this database for matching crop, tillage system, and county. The final selection from the matching pool of candidate templates was fully random as there are no data with which to dictate a preference between templates matching the criteria.

Simulation

The sampling procedure described herein reduces the theoretical number of HRUs needed to represent the U.S. without bias due to selection thresholds, but a very large number of simulations were still needed to provide a statistically adequate number of samples for any given locational unit query. Each sample was independently drawn from the population of all potential HRUs; therefore, each simulation is also independent. This allows a large number of simulations to be performed in parallel. Each SWAT simulation is five years in length with a two-year warm-up. The starting year for each simulation is randomly selected from 1965 to 2004. Predictions are reported as annual average values. With five-year simulations, it is likely that multi-year droughts or other weather patterns will significantly contribute to the average annual value. Coupled with the random start year, this allows some climate variability to be imposed upon the resulting database. This allows some inferences to be derived from this database with respect to prediction uncertainty due to climate, although this is not presented in this manuscript.

Software. Specialized software was developed to draw a sample from the population of HRUs and construct a corresponding SWAT model. A conceptual diagram is given in Figure 1. Model inputs and distributional information are stored in a Microsoft Access database. A model constructor uses this database to draw a sample and construct a SWAT model. The methods used to construct the simulations were derived from TBET (White *et al.*, 2012). The SWAT model is executed, and the model constructor extracts relevant outputs and uploads them to a common Microsoft SQL for database on a remote server. The model constructor then repeats the process until instructed to stop. The Microsoft SQL database can be queried at any time by a custom query engine which provides summaries by county or HUC-8. All programs were written in Microsoft Visual Basic.NET.

Hardware. Simulations were performed using a dedicated computer cluster. The cluster consists of multiple servers running windows server 2008 and Microsoft SQL for database services. There are 23 computational nodes running Microsoft Windows 7

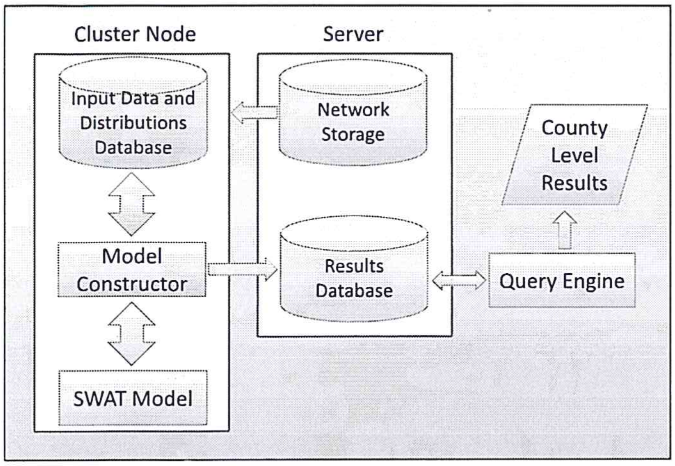

FIGURE 1. Conceptual Software Diagram.

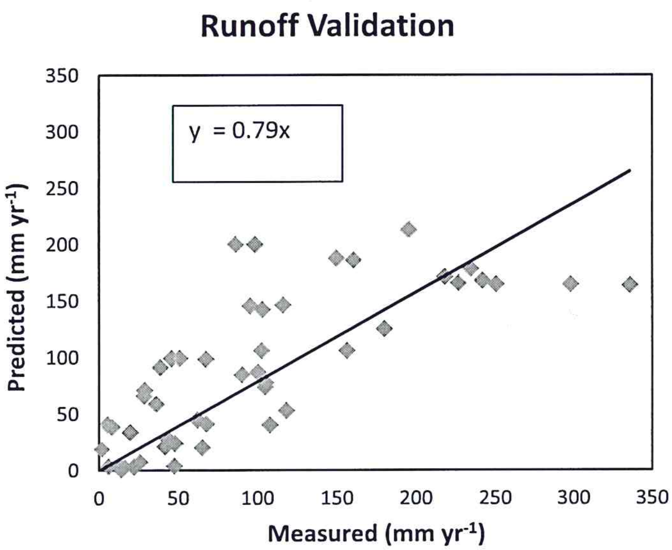

FIGURE 2. Measured and SWAT Predicted Edge-of-Field Runoff. Includes 52 data points comprised of 331 site years in Oklahoma, Arkansas, Texas, and Georgia.

Professional each with 8 GB RAM and 3.2-3.3 GHz quad-core intel processors. All computers communicate via a private gigabit network. Each node is capable of accommodating 12 active threads, allowing for a total of 276 simultaneous SWAT simulations. The system can perform 7 million simulations per day.

Model Validation

The procedure and parameters for the construction of SWAT models was derived from White *et al.* (2012), which employed calibration at both the watershed scale and field scales. This calibration was also ported over for this application. Although a different version of SWAT was used in this study (revision 592 *vs*. TBET specific revision), SWAT was not recalibrated for this application. Field scale data assembled for the calibration of TBET were used to evaluate the ability of the new revision to adequately predict runoff and thus the transference of hydrologic calibration parameter adjustments. These validation data were derived from the MANAGE database (Harmel *et al.*, 2006, 2008). A total of 331 site years of data from published and unpublished studies in Oklahoma, Arkansas, Texas, and Georgia were included in the validation. These monitoring sites include rangeland, pasture, wheat, sorghum, cotton, and corn. Slopes ranged from 0.5 to 16% and precipitation varied from 550 to 1,340 mm/yr. Sites were monitored for 1-16 years. An individual SWAT model for each monitored field was developed. These predictions were compared with average annual runoff at each site collectively (Figure 2).

The SWAT model used in the application reproduced runoff less successfully than TBET but still acceptable for this application ($R^2 = 0.50$). This is expected since the calibration applied here was developed with the TBET version of SWAT. The regression intercept was not significant ($\alpha = 0.05$) and the slope (0.79) indicates a tendency to under predict during high runoff conditions. The TBET version of SWAT exhibited the same behavior which was attributed to predicting surface runoff specifically; subsurface return flow was not included in these SWAT predictions. At monitoring sites, only total runoff was monitored, which would include both surface runoff and lateral subsurface return flow at many locations, especially larger fields. Overall relative error indicated that SWAT under predicted flow by 7%. One noted limitation of this validation is that monitored fields are located in the south and central U.S., not uniformly distributed throughout the U.S.

White *et al.* (2015) used a similar but expanded approach to validate a very similar modeling effort. That work required additional validation for sediment and nutrient losses, which are not examined in the present study. Other studies have used more abundant stream gage data for calibration or validation (Schuol *et al.*, 2008; Faramarzi *et al.*, 2009; Huang and Li, 2010). The use of streamflow monitoring data is not compatible with the approach utilized in this research, as each simulation is an individual HRU representing a single field. No attempt to aggregate multiple fields in the same model or incorporate routing was included.

Sample Database

A total of 21 million SWAT simulations were performed using the system discussed previously. These data are kept in a Microsoft SQL database which can be queried at a variety of spatial scales. As the distributional information underlying the sampling scheme is based on available data; samples queried based on any particular spatial unit are representative of the distributions within that unit. With 21 million samples and approximately 800 million ha of land in the area of interest, each sample represents roughly 38 ha. For example, if we query the database of 21 million samples for the HUC-8 1105002 (Lower Cimarron-Skeleton) 23,000 samples are returned. Thirty-seven percent of these are cropland of various types, 16 differing land uses are represented and 5% of the area is irrigated. The average surface runoff across all samples was 87 mm/yr, which represents the average value for this particular HUC-8. We could further refine the query for a particular land use by selecting winter wheat, of which there are 7,879 samples, with an average surface runoff of 52 mm/yr. We could extract the full distribution of surface runoff (or any other model output) across the sample query, but for this research only mean values were utilized.

Blue and Green Water Calculation

The definition of blue and green water and crop VWC are well defined, but the actual calculation varies somewhat within the existing research. The primary discrepancy being what portion of the annual ET should be included. Some references specify that only actual crop ET during the growing season be included (Huang and Li, 2010; Sun *et al.*, 2012), which limits the included amount of ET to between 100 and 300 days per year. ET outside the growing season is not considered, even though it certainly has an impact on the system. To develop holistic water balances required for this research, we contend that annual average ET is best for our application for several reasons. First, once land has been devoted to the production of a particular crop or crop rotation, it cannot be used for other purposes. ET from the entire production cycle should be considered. An industrial analog would be that the cost of electricity to heat and cool a factory at night when workers are not present must be accounted for in the total cost of producing a product. Second, our goal includes the assessment of net blue water balance by HUC-8 on an average annual basis. The use of annual values lets us better account for blue water production (runoff and aquifer recharge) outside the crop season. Third is our analysis is not strictly limited to cropland, at the HUC-8 level, we must consider noncultivated areas without defined growing seasons. Other researchers have also elected to use average annual ET (Schuol *et al.*, 2008; Faramarzi *et al.*, 2009). For the purposes of this research, we define blue water use for cropland is the sum of all irrigation applications, and green water use as the actual ET less blue water use. Blue water production is the sum of deep aquifer recharge and total water yield (sum of surface runoff, groundwater contributions to streamflow, and lateral soil flows). Net blue water balance is blue water production less blue water use, and may be negative in locations which import blue water or use more groundwater than is replaced via recharge.

HUC-8 Water Balance

The SWAT model predictions were used in combination with county water use data compiled by the USGS for 2005 (Kenny *et al.*, 2009) to develop a net water balance by HUC-8. SWAT predictions alone could not be used as the current system considers only irrigation demand, not water used for municipal water and other purposes. County level water used data were converted to a per unit area basis and resampled at the HUC-8 level. These data contain both surface water and groundwater usage. Surface water usage was combined with SWAT predicted surface runoff, lateral, and groundwater flow to estimate net surface blue water balance. Groundwater usage data were combined with SWAT predicted aquifer recharge to estimate the net blue groundwater balance.

Predicting Crop Virtual Water Content

Virtual blue and GWC of commodity crops was predicted by combing SWAT hydrologic predictions from the sample database with reported county crop yield statistics. This hybrid approach of simulation and reported statistics was also used by Huang *et al.* (2010). Crop VWC for corn, wheat, soybeans, and sorghum were evaluated across the contiguous U.S. at the HUC-8 level.

NASS grain yield data were obtained for the period 1990-2009. These data are reported at differing spatial scales including counties, agricultural districts (groups of counties), state, and the national level. An average yield for 1990-2009 for each county was developed using a combination reported county yield by year supplemented with district yield by year (when county records are not available). Counties lacking sufficient yield data for a particular crop were excluded from analysis for that crop. In general, this indicates that crops are not grown there, or production is very small. These data were resampled at the HUC-8 level to be spatially coincidental with the previous HUC-8-based water balance. Blue and green water use was derived by querying the SWAT predictions database by crop and HUC-8. Blue water consumption was taken as the SWAT predicted irrigation volume. Green water use was the average annual ET less blue water use. These data were combined with crop yield to derive the total crop VWC, BWC, and GWC. BWC was further subdivided based on the local surface/groundwater balance at the HUC-8 level. BWC was allocated among renewable and nonrenewable sources.

RESULTS AND DISCUSSION

Water Balance

Water availability and use vary greatly across the U.S. SWAT predicted annual precipitation, irrigation, surface runoff, and ET are given in Figure 3. Precipitation was greatest in the Southeast, Atlantic Coast, and Pacific Northwest. Surface runoff is driven by precipitation and shows a similar pattern. ET showed a similar pattern with the addition of temperature effects. ET was reduced in northern latitudes along the East Coast most likely due to lower summer temperatures. Irrigation application was inversely related to precipitation and compounded by water availability. Irrigated areas stand out in a band from Texas to North Dakota, the California Central Valley, and isolated pockets throughout the western U.S.

SWAT predictions were combined with USGS estimated water usage to develop net water balances for surface and groundwater by HUC-8 (Figure 4). Overall, the U.S. has a net surplus of blue water, on average 280 mm/yr of blue water are available, but the distribution is highly variable. Available blue water resources and the need for such resources by agriculture and municipalities are not coincidental. The net balance is not always positive, indicating that use is greater than sustainable local availability.

Net surface water balance by HUC-8 is also given in Figure 4. Positive values indicate that there was

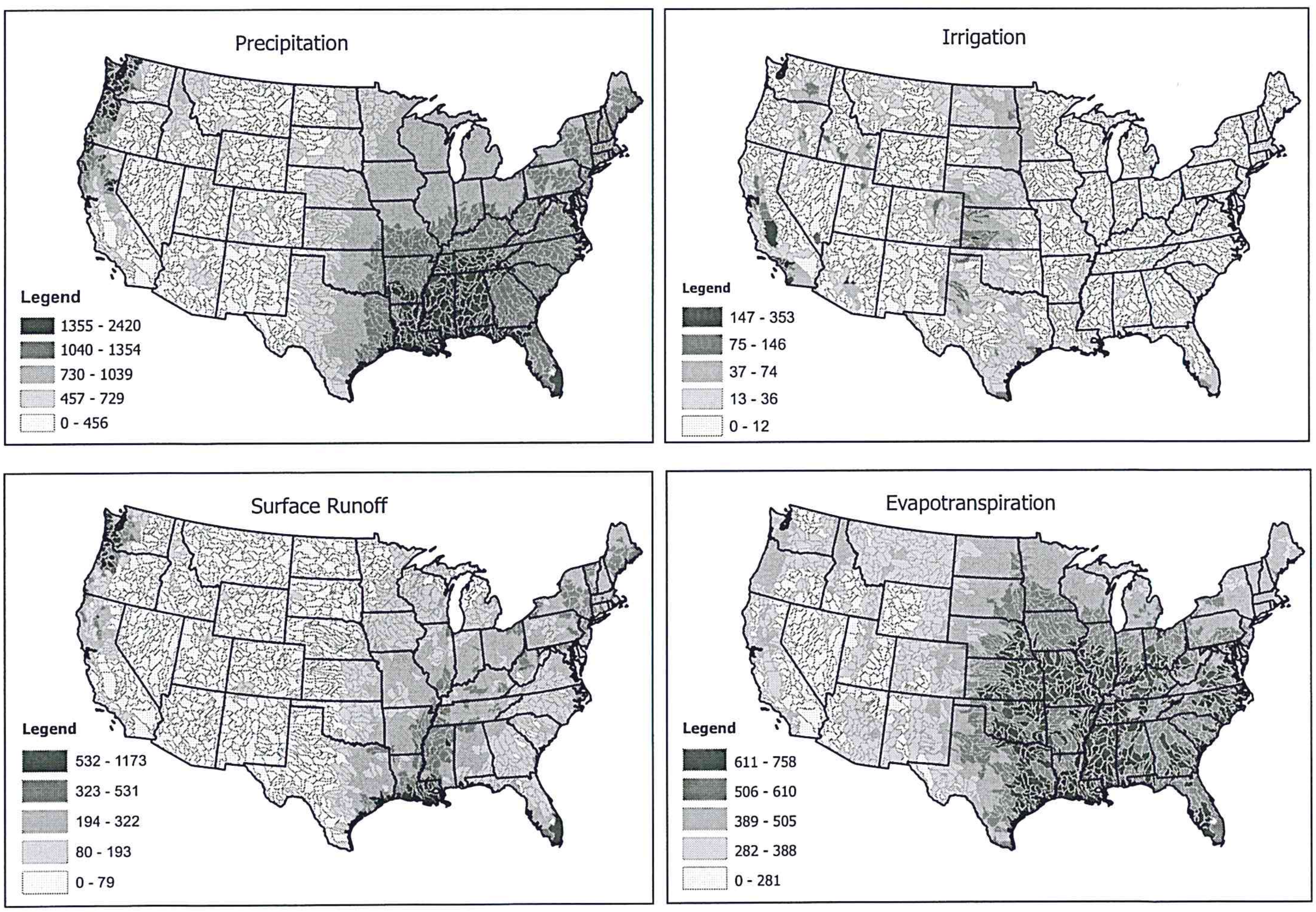

FIGURE 3. Predicted Average Annual Precipitation, Irrigation, Surface Runoff, and Evapotranspiration (in mm/yr) by HUC-8 for the U.S.

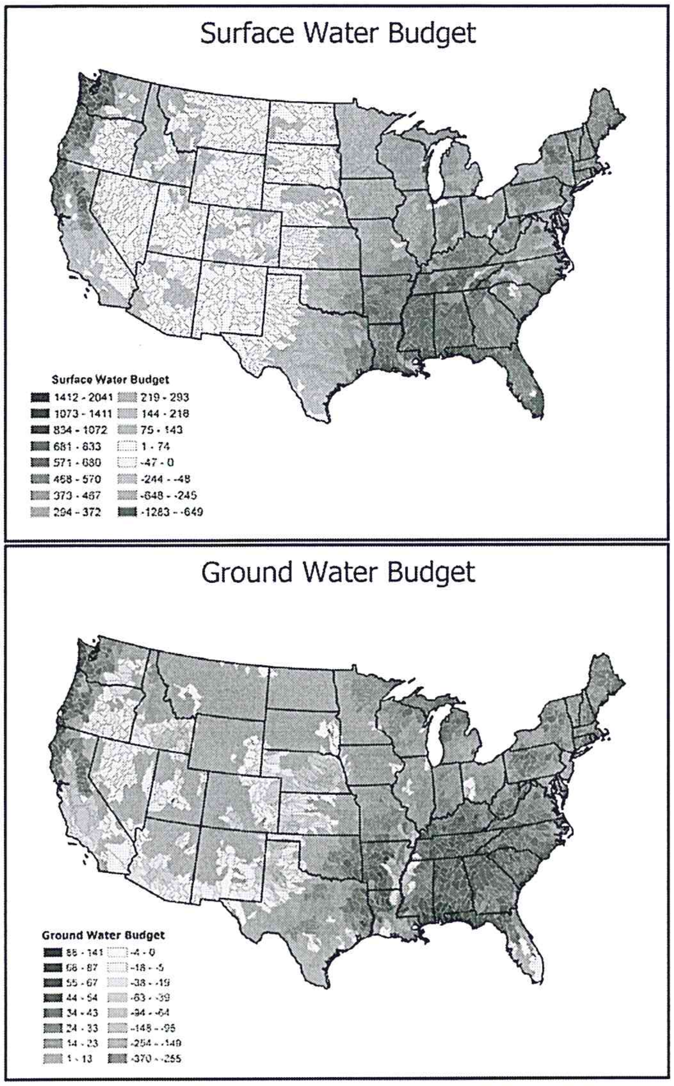

FIGURE 4. Net Blue Water Balance (in mm/yr) by HUC-8 for the U.S. Displayed as Surface Water Budget (top) and Groundwater Budget (bottom).

more blue surface water generated via runoff to lakes, reservoirs, and streams than is used within the HUC-8. Negative values indicate that usage exceeds local availability and that surface water is imported from another HUC-8. Small pockets of negatives throughout (particularly in the Northeast) are due to the presence of urban centers with large water demands. The source of this water use may be a river or reservoir within the HUC-8, but the water originates upstream from outside the HUC-8. The water may be conveyed to the HUC-8 either naturally by river or via aqueducts, this analysis makes no distinction. Many larger pockets of the western U.S. also use more surface water than can be sourced locally, including the California Central Valley and the Snake River Valleys.

Net blue groundwater balance is also shown in Figure 4. Of particular interest are HUC-8s where the balance is negative, indicating that groundwater usage exceeds aquifer recharge as predicted by SWAT. This depletion use can only occur where groundwater reserves of fossil water exist, and cannot continue indefinitely. Several large regions of groundwater depletion are apparent; each is underlain by a known aquifer of concern.

A large area of depletion occurring in the western Midwest covering portions of Nebraska, Colorado, Texas, Oklahoma, and Kansas lies above the High Plains aquifer system. Usage in this area was predicted to average 58 mm/yr with only 4.6 mm/yr of recharge. Some HUC-8s had depletion greater than 150 mm/yr. From 1950 to 2007, the average water level in the High Plains declined by 4.2 m (McGuire, 2009). While this decline is not directly comparable to net blue water balance, it does corroborate that the modeling system does identify known regional water imbalances. A more direct comparison with existing literature was made using the ratio use and recharge, which is equivalent to the groundwater footprint as defined by Gleeson *et al.* (2012). The value predicted in this research (12.6) is similar to the findings of other research in the high plains. Esnault *et al.* (2014) calculated the groundwater footprint using Scanlon *et al.* (2012), Faunt (2009), and Gleeson and Wada (2013). They predicted average values for the Central High Plains to range from 8.2 to 13.6, a range than encompasses the predicted value of 12.6 in this study.

Other regional deficiency occurs in western Arkansas along the Mississippi river, and the California Central Valley. Twenty-four percent of the U.S. uses groundwater faster that it is replenished, and 5% of the U.S. regions depleted groundwater at a rate of 50 mm/yr or more.

Crop Virtual Water Content

VWC is a useful benchmark to contrast local and national crop water management. Overall predicted VWC ranged from 762 to 2,261 m^3/ton. Other researchers have reported VWCs for various crops in differing locations in both the U.S. and worldwide. Eight studies were selected for comparison purposes (Table 2). The VWC data presented in this study are not directly comparable to most existing literature as they are computed in different ways. For reasons described previously, we elected to use average annual ET instead in this study to allow us to make inferences about total annual water budgets, other researches elect to use ET within the growing season only. For this reason our predicted crop VWC are

TABLE 2. Predicted Total, Blue and Green VWC of Selected Crops Produced in the U.S. All units in m^3/ton.

Source	Corn	Wheat	Soybeans	Sorghum
Virtual water content				
This study	762	2,137	2,261	1,480
Literature average[1]	648	1,379	1,691	1,902
Deviation	18%	55%	34%	−22%
Literature range[1]	370-1,222	588-1,911	1,081-2,145	765-3,048
Sun *et al.* (2012)[1]	830	1,071	—	—
Zwart and Bastiaanssen (2004)[1]	555 (370-909)	917 (588-1,666)	—	—
Hanasaki *et al.* (2010)[1]	621	1,359	1,921	—
Mubako and Lant (2013)[1]	538	1,394	1,081	756
Mekonnen and Hoekstra (2011)[1]	1,222	1,827	2,145	3,048
Oki and Kanae (2004)[1]	466	1,911	1,718	—
Aldaya *et al.* (2008)[1]	466	1,707	1,414	—
Chapagain and Hoekstra (2004)[1]	489	849	1,869	—
Green water				
This study	715	2,043	2,193	1,449
Hanasaki *et al.* (2010)[1]	560	1,099	1,839	—
Aldaya *et al.* (2008)[1]	367	1,028	1,175	—
Blue water				
Surface local (this study)	7	17.1	20.1	4.4
Surface imported (this study)	4.4	11.8	0.3	2.2
Groundwater renewable (this study)	4.9	7.3	36.6	3.3
Groundwater depletion (this study)	30.7	57.1	10.7	21.3
Total (this study)	47	93.3	67.7	31.2
Hanasaki *et al.* (2010)[1]	62	261	82	—
Aldaya *et al.* (2008)[1]	99	679	239	—

[1]Limited to growing season ET.

TABLE 3. Total Predicted Annual Water Consumption of Selected U.S. Crops by Source. All units in km^3/yr.

Crop	Green	Blue Surface Local	Blue Surface Imported	Blue Groundwater Renewable	Blue Groundwater Depletion
Corn	178	1.8	1.1	1.2	7.6
Wheat	123	1.0	0.71	0.44	3.4
Soybeans	159	1.5	0.025	2.7	0.77
Sorghum	19	0.06	0.030	0.044	0.28
Total	480	4.3	1.9	4.4	12

somewhat larger. On average, VWC predicted in this study was 30% greater than the literature average, with the exception of sorghum. Only two of the eight existing studies we examined included sorghum. The study by Mekonnen and Hoekstra (2011) was world-wide and likely includes conditions atypical of the U.S. environment. The VWC value was much higher than that listed by Mubako and Lant (2013) for the U.S. average sorghum value (3,048 *vs.* 756) and skewed the literature average in our analysis. We attribute much of this deviation between the crop VWC in this study and literature to the inclusion of outside the growing season ET. Wheat which showed the largest difference is primarily a cool season crop, which means that relatively high ET during the summer is not considered by most literature estimates. Reported literature values also have a very large range, indicating the inherent regional variability associated with VWC.

Aldaya *et al.* (2008) and Hanasaki *et al.* (2010) further separated VWC into blue and green fractions for the U.S. VWC derived from these studies, which were limited to the U.S., are between 36 and 40% lower than this study, again presumably due to growing season *vs.* annual-based ET summaries. Both blue and green water VWC were lower in this study, but there is also considerable variance in previously reported estimates between Aldaya *et al.* (2008) and Hanasaki *et al.* (2010).

VWC and U.S. production data were used to estimate the total virtual water contained in these crops. The total water consumption for the entire U.S. production is given in Table 3. The vast majority (95%) of the virtual contained in these crops is green. Less than 1% (0.86, 0.87) is derived from locally sourced surface water and renewable groundwater, respectively. Imported surface water accounts for 0.37%. The high opportunity cost of importing surface water

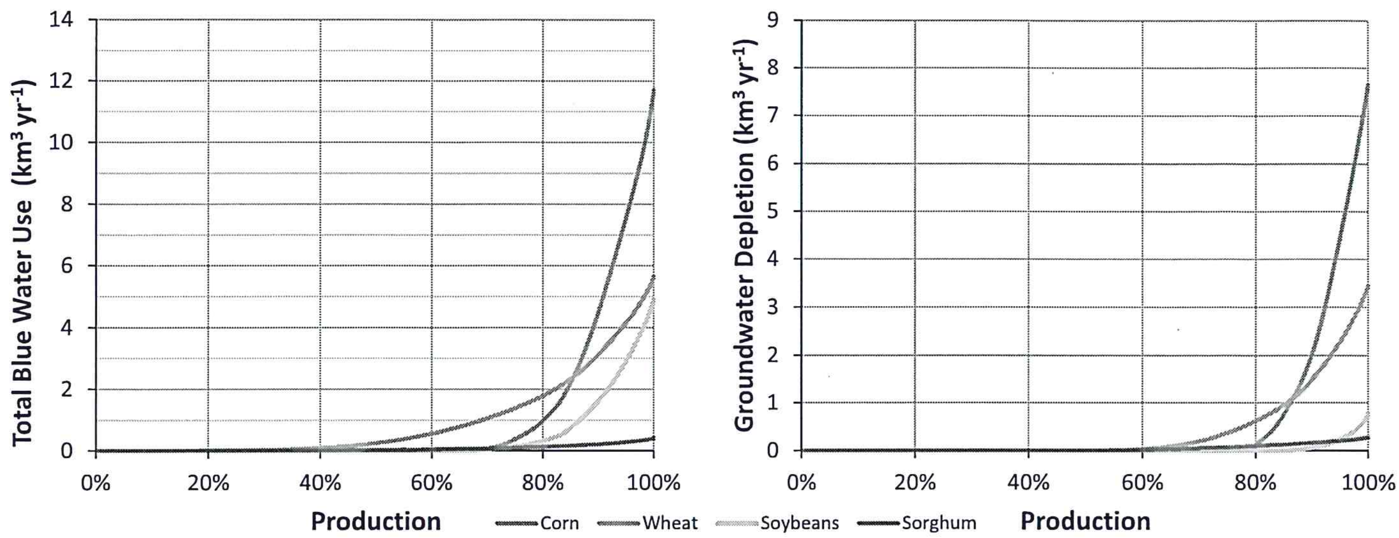

FIGURE 5. Annual Blue Water Consumption *vs*. Cumulative U.S. Total Crop Production.

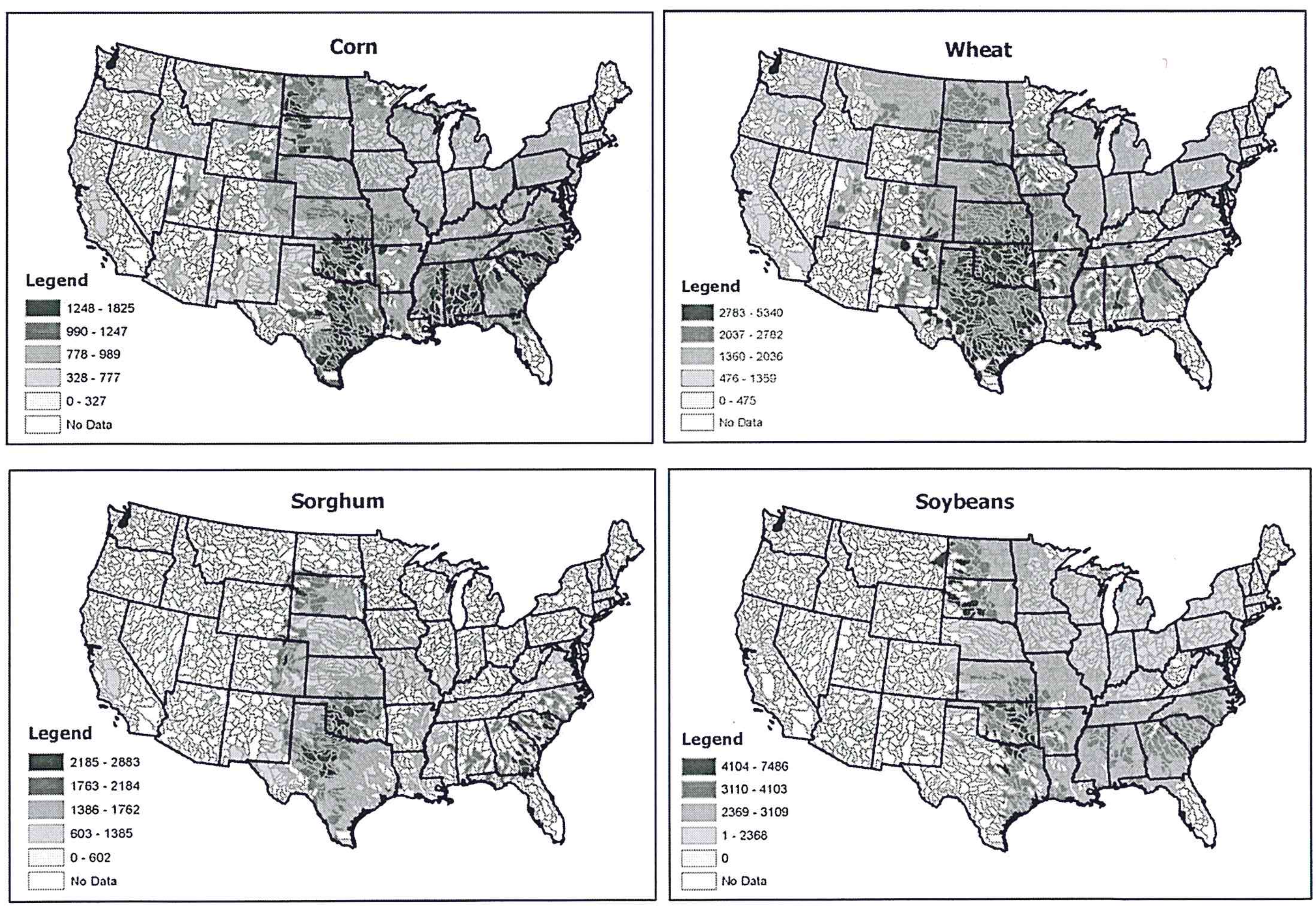

FIGURE 6. Virtual Crop Water Content in m^3/ton.

may limit its use on these relatively low value crops. We expect that high value vegetable and fruit crops would have a much higher percentage. Blue water from groundwater depletion accounted for 2.4% of the virtual water in these crops, and 53% of all blue water used in their production. The total U.S. produc-

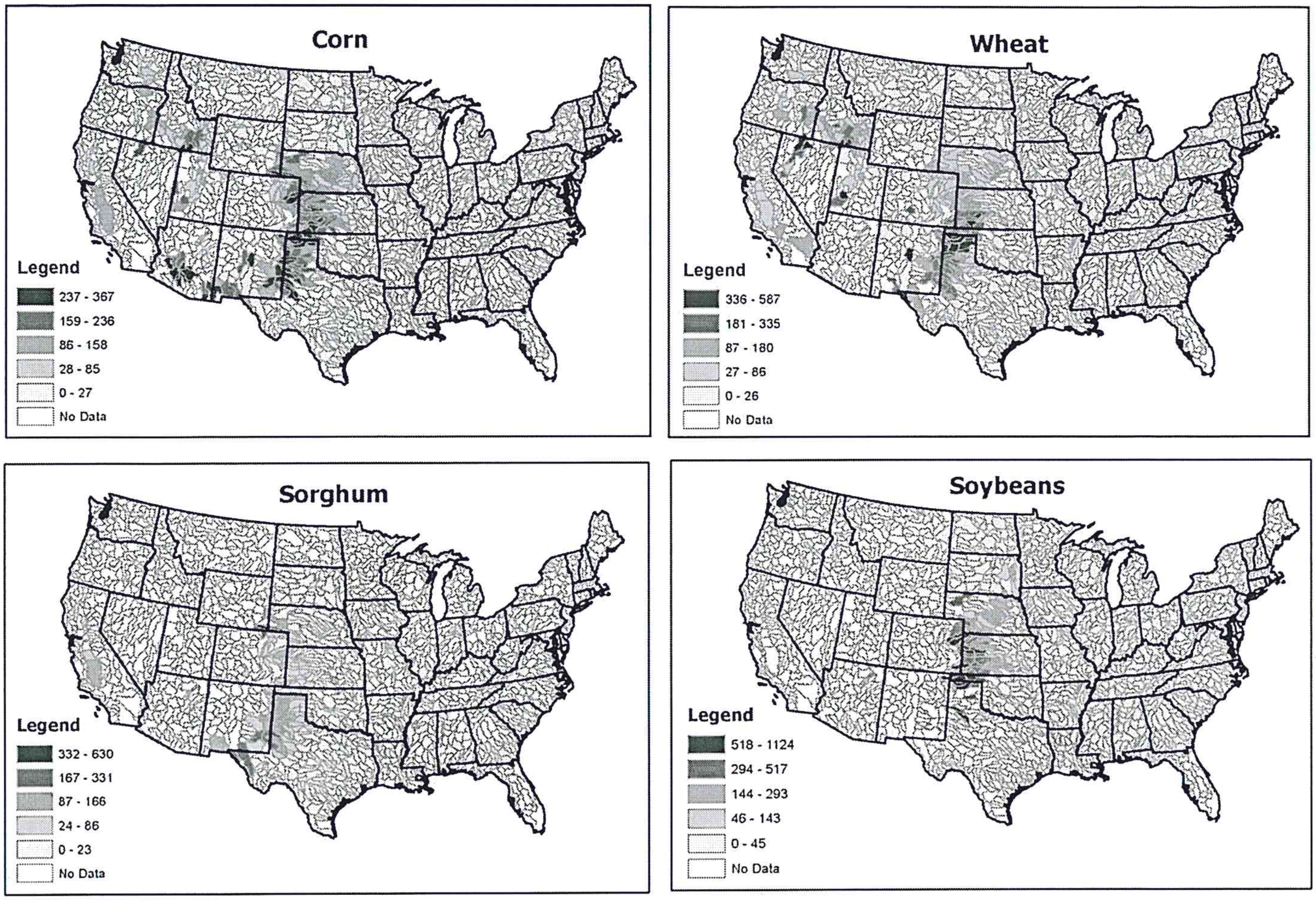

FIGURE 7. Blue Virtual Crop Water Content (BWC) Sourced from Groundwater Depletion in m^3/ton.

tion of these four crops used 502 km^3 of virtual water each year.

Total irrigation usage by agriculture was predicted to be 99 km^3/yr. Other researchers have estimated somewhat greater irrigation water use in the U.S. Liu and Yang (2010) estimated 117-138 km^3/yr which is similar to the 139 km^3/yr predicted by Siebert and Doll (2010). Wisser *et al.* (2008) predicted a slightly wider range of 96-140 km^3/yr, which covers the value in the present study. One contributing factor for this apparent underprediction is that conveyance losses were not included in the SWAT simulations for cultivated agriculture as SWAT simulations were performed at the field scale. These additional losses are included in the overall water use data used in HUC-8 water balances which is based on estimated withdrawals, not irrigation demand. The total amount of water usage (all demands including irrigation and other uses) from nonrenewable groundwater was predicted to be 58 km^3/yr, of this 21 km^3/yr was used for irrigation of cultivated crops. Wade *et al.* (2012) estimated the total irrigation from nonsustainable groundwater to be 30 km^3/yr. Given the uncertainty in local recharge rates and irrigation usage, we consider this a favorable comparison.

Spatial Variability

There was considerable variability in both the VWC of crops and its source. Figure 5 illustrates total crop blue water usage and blue water from groundwater depletion as a percentage of total U.S. crop production. These data are ranked by increasing water use, to illustrate how much of the current crop is produced at a given level of blue water use. These data should not be used to estimate production declines resulting from restricted water use as they represent current conditions only.

Corn production was the largest user of blue water, consuming 12 km^3 per year, 7.6 of which was nonrenewable groundwater. Seventy-five percent of corn production used virtually no blue water; primarily in the Midwestern Corn Belt where growing conditions require little irrigation. Wheat and soybeans were the next largest consumers of blue water. The

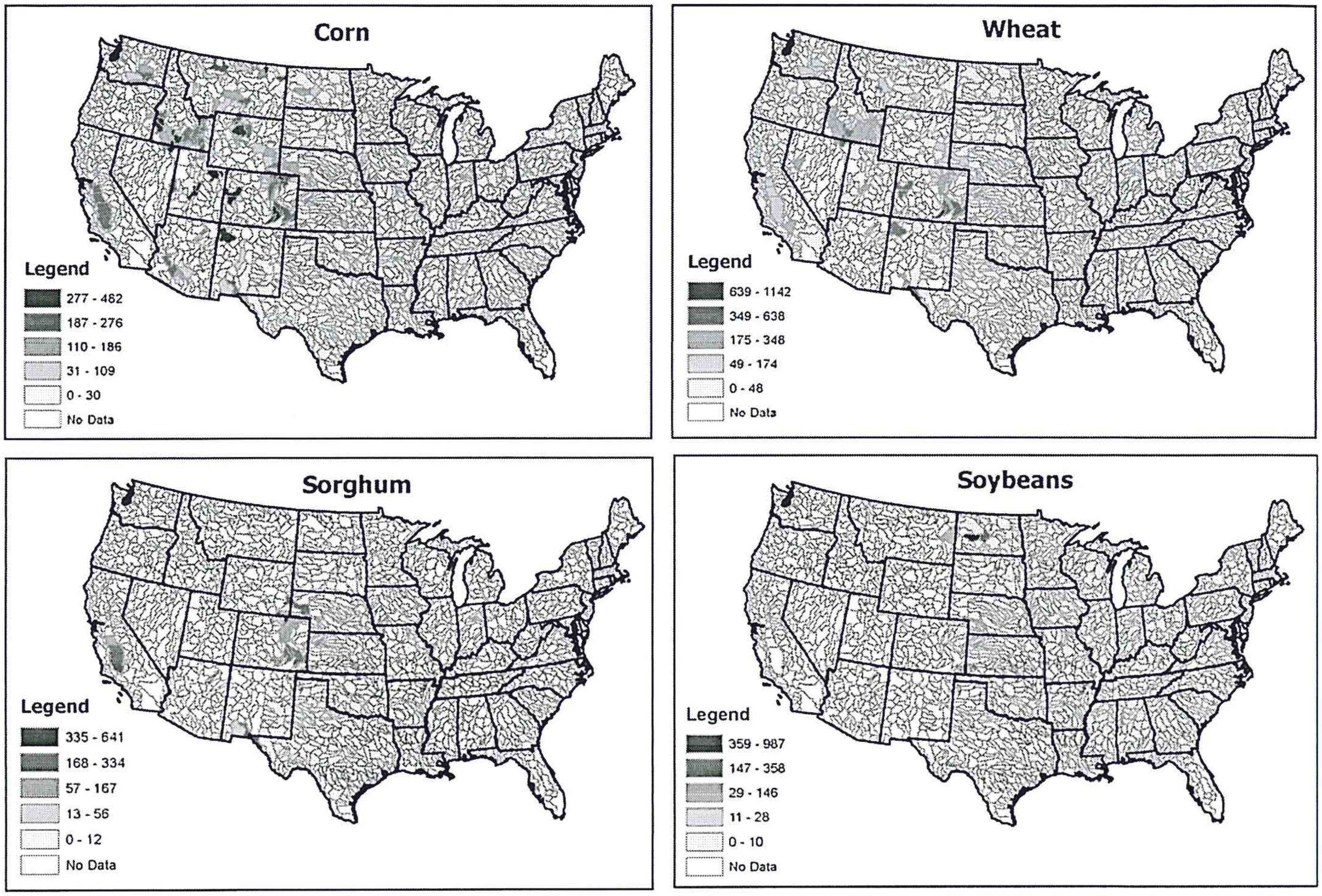

FIGURE 8. Surface Water Import by Crop Type in m^3/ton of Production.

gradual slope of the wheat blue water use curve indicates that it is more commonly irrigated at a low level, perhaps supplemental irrigated to mitigate droughty conditions where it is produced. The soybean and corn curves are more abrupt with a defined inflection point. Most of the production of these crops (75-80%) is dryland. The remainder is highly dependent on irrigation, and water use increases in a linear fashion with production. Despite similar total blue water use, soybeans and wheat differ in their groundwater depletion. This is likely due to the differing irrigation sources in dominant production regions. Soybean production makes much greater use of surface water sources. Sorghum production accounted for only minor blue water usage.

There are regional trends in crop VWC and sources. Total VWC (Figure 6) includes green and all sources of blue water. In general crops grown in the southern U.S. have greater VWC than those in the North. The most efficient region to grow corn lies in the Corn Belt. Corn production in irrigated areas of the West also has a fairly low total VWC. Wheat and sorghum production in Oklahoma and Texas had the greatest VWC.

The total crop VWC is in general less important than the source of the water from a water resource perspective. BWC derived from the depletion of groundwater is shown in Figure 7. Groundwater depletion attributable to soybean and sorghum production is almost exclusively limited to the High Plains. Both corn and wheat show the same pattern of depletion in the High Plains, with the addition of pockets of depletion throughout the western U.S. These patterns generally follow the availability of groundwater for irrigation in the West and Midwest. Groundwater was not depleted in the eastern U.S. due to the production of these four crops. Figure 4 does show an area of groundwater depletion in western Arkansas along the Mississippi river valley. Extensive rice production in this region is the likely cause. Rice production was included in these simulations but not isolated for individual analysis in Figure 7.

Imported surface water is also a valued blue water source due to both its limited availability and infrastructural costs associated with transport. These data are illustrated in Figure 8. Sorghum and soybeans accounted for very little (<3% combined) imported surface water use. Imported surface water use was limited almost exclusively to the western U.S. for corn and wheat production. Use was especially heavy in major river valleys including the Snake, Missouri, Platt, Colorado, Arkansas, Salt, and San Joaquin. River water which originates upstream outside the HUC-8 can be used locally with less transportation cost.

SUMMARY AND CONCLUSIONS

This study utilized the SWAT model to predict hydrologic budgets for each HUC-8 in the U.S., and the use of blue and green water resources by four commodity crops. This novel approach of distribution sampling and model construction allows data at various spatial scales to be integrated and used in a computationally effective manner. The database of 21 million samples represents many combinations of soils, topography, land use, and management. This dataset can be queried by crop, ecoregion, or HUC-8 with distributional fidelity. These simulations were combined with existing crop yield statistics and water use data to predict local HUC-8 water balances, the VWC of four major crops and the source of water used to grow them.

The vast majority of the VWC of U.S. crops were green, derived from rainfall alone. The amount of water needed to produce a ton of grain varied regionally. In many regions, crops were produced with blue water (irrigation) from a variety of sources. Blue water use was subdivided into local and imported surface sources and groundwater. Groundwater use less than the recharge rate is sustainable; anything more is nonsustainable groundwater depletion. The production of these crops was estimated to deplete groundwater by 12 km^3/yr, most of that usage in the High Plains. Konikow (2013) estimated that 10 km^3/yr were depleted from the High Plains from 2000-2008 and that 992 km^3 had been depleted from major U.S. aquifers since 1900. Once gone, the overlying agricultural and urban landscapes must change. It is critical that we manage these resources wisely while we have the opportunity to do so. Western water rights are controversial, complex, and litigious. Municipalities and agricultural producers will continue to compete for this limited resource. This research is an effort to aid decision makers in this process by informing them of how much water is in the grain we consume and export at the regional level, and how much of that water is nonrenewable. This information can be used to inform debate on where and how we should be producing grain.

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